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China can peak its energy-related carbon emissions before 2025: Evidence from industry restructuring

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ABSTRACT

China has committed to a peak in carbon dioxide emissions circa 2030. However, current policies cannot meet this ambitious goal. Adjusting its energy-intensive, heavy and chemical-based industrial structure is not only the main way China can change its economic growth pattern but also a key policy strategy to achieve its carbon emission peak goal. In addition to carbon emissions goals, economic growth and employment security must be considered for China's development in the context of addressing climate change. Hence, by proposing a new economic-carbon emission-employment multi-objective optimization model, we take a different approach to analyze China's emissions trajectory. The optimized results show that China's energy-related carbon dioxide emissions could peak between 2022 and 2025, most likely in 2023, with CO_2 emissions of 11.21–11.56 Gt. When pursuing this peak (from 2013 to 2030), China could still maintain an average growth of approximately 6.1 to 6.4% yr^{-1} for GDP and approximately 0.24% to 0.51% yr^{-1} for employment. Furthermore, China's coal consumption has peaked in 2013 while oil would be peaked around 2023 to 2025, based on the optimized industrial structure adjustment trajectory from 2013 to 2030.

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1. Introduction

China's carbon emission has sharply increased over the past 20 years because of the country's energy-intensive, heavy and chemical industry-based growth model and its coal-dominated energy consumption structure. As China is the largest carbon emitter in the world, a peak in its carbon emissions would substantially contribute to the goal set in the Paris Agreement, which limits global warning to less than 2 °C by 2100 (compared with the pre-industrial level). Over the past few years, the Chinese economy has entered a "new normal", characterized by a continuous drop in the GDP growth rate since 2013 and a decrease in coal consumption from 2014 to 2016 (NBSC, 2017). As a result of these changes, China's carbon emissions growth is slowing down or even declining (IEA, 2016). However, because of tenuous data, it remains highly uncertain whether the decline in coal consumption is short term or long term (Korsbakken et al., 2016). A series of emission reduction policies has been issued in recent years (CSDRC, 2014; CSC, 2016a, 2016b, 2017), but a large number of studies clearly show that China cannot achieve a carbon emissions peak by 2030 under the business-as-usual policy scenario (Den Elzen et al., 2016; Hao and Wei, 2015; Niu et al., 2016; Yuan et al., 2014; Zhang et al., 2016). Therefore, more effective reduction measures must be adopted for China to reach its carbon emission peak by 2030.

At the macro level, carbon emissions can be cut through three strategies: a scale effect, a technology effect and a structure effect. Reducing the scale of GDP or the population can effectively reduce carbon emissions; however, this is not a desirable way to achieve peak emissions in any country, especially a developing country such as China. Improving energy use efficiency through a technology effect (for example, converting traditional coal-fired plant technology, subcritical plants, into integrated gasification combined cycle in coal-fired plants) has been the primary contributor to the decrease in China's carbon emissions growth rate in the past decade (Guan et al., 2014; Su and Ang, 2017). However, the structure effect—which involves adjusting the output structure (for example, cutting the output of carbon-intensive sectors but increasing the output of less carbon-intensive sectors) or mixing energy sources (such as substituting high carbon coal with non-fossil fuels)—has contributed little to China's carbon emission reduction and has even been counterproductive (Su and Ang, 2015; Wang et al., 2013; Zhang et al., 2009). The root cause of these results is China's irrational industrial output structure. In pursuit of maximum local GDP growth, investment in a large number of heavy-industry

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and carbon-intensive production factories (such as steel and cement production) has been encouraged by Chinese local governments (Green and Stern, 2017). As a result, especially in the secondary industry, the industrial structure has transformed from being dominated by low energy consumption sectors to being dominated by high energy consumption sectors (Guan et al., 2014; Zeng et al., 2014). Obviously, these changes in economic structure conflict with China's efforts to reduce carbon emission. Therefore, properly adjusting China's industrial structure and fully tapping the carbon emission potential produced by restructuring are key strategies for China to achieve its carbon emission peak.

Studies of China's carbon emission peak have focused on setting scenarios according to various Kaya components, such as economic growth, energy efficiency, carbon intensity, and urbanization (den Elzen et al., 2016; Gambhir et al., 2013; Niu et al., 2016), to investigate the likelihood that China will achieve a CO_2 emissions peak by 2030. Strategic policies have also been proposed to reach this goal (He, 2014; Liu et al., 2016; Liu et al., 2015a). However, in related studies, many factors are involved in scenario analyses. To avoid factor permutation, representative scenarios must be set, but there is considerable uncertainty regarding how to do so. Moreover, the structures of the three industries (agriculture, industry and services) have been merely summarized (He, 2014; Wang and Zou, 2014), and there is no detailed investigation of the relationship between structural changes and the emission peak.

Industrial structure adjustment is a constrained multi-objective problem. The essence of industrial restructuring is a sustainable development issue that shifts the conventional extensive growth mode toward a more intensive growth pattern. The core task of the adjustment is to coordinate economic benefits and ecological environmental protection. Reducing carbon emissions is not the sole objective of industrial adjustment; economic development and employment security are also very important objectives for the country with the world's largest population. Furthermore, the adjustment seeks not only to cut the output of high-emission sectors but to increase the output of lower-emission sectors. In the process of adjustment, the input-output balance law of the socio-economic system must be followed. Constraints such as sectors' output capacity, available total energy supply, and available labor supply should also be considered to achieve coordination among various sectors. Clearly, industrial structure adjustment is a constrained multi-objective optimization problem. Here, we adopt a different approach, a new economic-carbon emission-employment multi-objective optimization model, to explore how to achieve China's energy-related carbon emission peak by industrial restructuring. The effects of output structure changes in 32 economic sectors (listed in Table A1) on carbon emission are investigated. Furthermore, to ensure that the peak is reached, the direction and efforts of sectoral output structure changes are clarified.

2. Methods and data

2.1. Economic-carbon emission-employment multi-objective optimization model

2.1.1. Model assumptions

Multi-objective optimization model can derive trade-off between economic and environmental objectives subject to constraints. The model can avoid some issues of econometric modeling, such as heteroscedasticity, autocorrelation, multicollinearity, etc. (Chen, 2001). As a result, the particular model has also a wide variety of applications in energy and environmental problems as well as in issues that are related to the sustainable development in general (da Silva and Marins, 2014; Dong et al., 2014; Edenhofer et al., 2013; Yu and Gao, 2016; Yu et al., 2017). The model for the problem to be solved in the present paper is based on three assumptions. Firstly, energy utilization technology is exogenous. Energy intensity (energy consumption per unit value added) follows the change pattern from 2011 to 2016, and data from 2017 to 2030 are forecast based on an extrapolation of historical trends. Secondly, the basic assumptions for the input-output model, such as only one type of product in each sector and constant returns to scale are also followed. Finally, we only consider the carbon emissions from fuel combustion, regardless of the carbon emissions from cement production and land use.

2.1.2. Objective functions

a). The minimum cumulative value of sectoral CO_2 emissions

The carbon emissions of the economic sectors account for the vast majority of China's total emissions. Therefore, for emission to peak circa 2030, the emissions of sectors must be controlled. Thus, the minimization of the cumulative value of sectors' CO_2 emissions between the base year and 2030 is set as the first objective—that is, the smaller the total amount of sectoral carbon emissions, the better, namely,

$$\min\ f_1 = \sum_{t=1}^{M}\sum_{k=1}^{K} p_k (C_k)_t (I - A_{ct}) X_t \tag{1}$$

where $K = 4$; k = 1, 2, 3, 4 represent coal, crude oil, natural gas and primary electricity; M represents the years of the planning period; p_k denotes the CO_2 emission coefficients of energy k; $(C_k)_t$ is the sectors' energy consumption per unit value-added of energy k in year t; X_t is the sectors' output vector in year t; A_{ct} represents the diagonal matrix composed of the contribution coefficient of intermediate input (a_{cj}) $(j = 1, 2, \ldots, N)$ in year t;N is the number of sector; I represents the identity matrix.

b). The maximum cumulative value of GDP

Economic development must be guaranteed while controlling the amount of CO_2 emissions. Thus, the maximum cumulative value of GDP in the planning period is considered as the second objective, namely,

$$\max\quad f_2 = \sum_{t=1}^{M} e(I - A_{ct}) X_t \tag{2}$$

where e represents the $1 \times N$ summation vector to aggregate the elements in the specified vector.

c). The maximum cumulative value of employment

It has always been one of the most challenging problems to guarantee employment stability and security, especially for China, a country with the largest population in the world. To make China decrease its CO_2 emissions and reach the peak, it is crucial to adjust the current industrial structure focusing on heavy industry. Supply-side structural reform and overcapacity elimination will inevitably affect employees in related sectors. However, structural adjustment necessitates efforts to promote an inter-sectoral labor shift so that full employment and social stability can be achieved. Hence, the maximum cumulative value of employment in the planning period is the third objective.

$$\max\quad f_3 = \sum_{t=1}^{M} L_t (I - A_{ct}) X_t \tag{3}$$

where L_t represents the sectoral workforce needed per unit value-added in year t.

2.1.3. Constraints

a). Dynamic input–output balance constraints

As a complicated whole, economic system have both close links and proportional relations between industrial sectors. Inter-sectoral relations—namely, a dynamic input–output balance between economic

sectors—must be taken into account during industrial structure adjustment.

$$X_t - A_t X_t = Q_t(X_{t+1} - X_t) + Y_{1t} + Y_{2t}, \quad t = 1, 2, 3, \cdots, M \tag{4}$$

where A_t is the technical coefficient of year t; Q_t is the investment coefficients; Y_{1t} represents the column vector of final consumption in year t; and Y_{2t} represents the column vector of net exports in year t. Different imports assumption has quite different impacts on the environmental input-output analysis, especially on the estimation of emissions embodied in exports (Su and Ang, 2013). China's input-output tables are compiled based on the competitive imports assumption. In this study, many used data derived from China's input-output tables. Therefore, to keep consistent in the data processing, the competitive imports assumption is made in the proposed model.

The constraints in Eq. (4) are a series of strict equality constraints that are difficult to satisfy, and this is the main reason for the instability of the multi-objective dynamic input–output optimization model. Two positive and negative deviation variables ($D_t^-, D_t^+ \geq 0$) of dynamic input–output balance in year t are introduced into Eq. (4) to change the strict equality constraints of the dynamic input-output model into inequality constraints (Yu et al., 2016) as follows:

$$X_t - A_t X_t = Q_t(X_{t+1} - X_t) + Y_{1t} + Y_{2t} + D_t^- - D_t^+ \tag{5}$$

The study regards the minimum sum of the positive and negative deviation variables as an objective to ensure overall economic balance. Therefore, the dynamic input–output balance constraints of the proposed model can be transformed into:

$$\min \sum_{t=1}^{M-1} e^T (X_t - A_t X_t - Q_t(X_{t-1} - X_t) - Y_{1t} - Y_{2t}) \tag{6}$$

b). Sectors' production capacity constraints

Obviously, CO_2 emission mitigation can be achieved by reducing the output of sectors with a higher carbon intensity and increasing the output of sectors with a lower carbon intensity. Nevertheless, in view of the economic system stability, inter-sectoral output adjustment should consider both dynamic input–output balance constraints and the sectors' production capacity, rather than adopt a causal perspective. Therefore, the output of each sector should be changed within a certain range.

$$\varphi_2 X_t \leq X_{t+1} \leq \varphi_1 X_t, \quad t = 0, 1, 2, \cdots, M-1 \tag{7}$$

where φ_1 and φ_2 represent the upper limits and lower limits of the sectoral output growth rate, respectively.

c). Economic growth constraints

Having maintained an annual growth rate of approximately 10% over the past three decades, China's economy has entered "new normal", in which economic growth has slowed down and turned toward quality-efficiency transforming and upgrading. However, as a developing country, China will face difficulty in achieving industrialization and modernization unless it maintains a high economic growth rate until 2030.

$$(1 + r_t) e(I - A_{ct} - 1) X_{t-1} \leq e(I - A_{ct}) X_t, \quad t = 1, 2, 3, \cdots, M \tag{8}$$

where r_t represents the minimum GDP growth rate in year t; X_0 represents the output of the base year.

d). The total energy consumption constraints

With economic development in the future, China's total energy demand will experience a certain amount of growth. Considering that carbon emissions are mainly caused by fossil energy consumption, the annual energy consumption growth must be limited within a certain range to reach the peak in a timely manner.

$$\sum_{k=1}^{K} (C_k)_t - (I - A_{ct}) X_t \leq E_t, \quad t = 1, 2, 3, \cdots, M \tag{9}$$

where E_t represents the maximum energy supply in year t.

e). Coal consumption ratio constraints

The coal-dominated energy consumption structure (average accounting for 70.8% of total primary energy consumption from 1990 to 2016) is an important reason for China's high carbon emissions. To reach the carbon emission peak, it is crucial to reduce the proportion of coal consumption in the total primary energy consumption in China and to increase the proportion of natural gas and non-fossil energy sources. Therefore, the proportion of coal consumption in primary energy consumption must be controlled to reach the peak.

$$\frac{(C_1)_t (I - A_{ct}) X_t}{\sum_{k=1}^{K} (C_k)_t (I - A_{ct}) X_t} \leq \alpha_t, \quad t = 1, 2, 3, \cdots, M \tag{10}$$

where $(C_k)_t$ is the $1 \times N$ vector of energy intensity coefficient, which represents energy k consumption per unit value added in year t, and α_t is the maximum proportion of coal consumption in total primary energy consumption in year t.

f). Labor supply constraints:

Employment security is an important prerequisite for China's economic transformation, but the total number of employees per year should be limited within the labor supply in the whole society.

$$L_t (I - A_{ct}) X_t \leq B_t, \quad t = 1, 2, 3, \cdots, M \tag{11}$$

where B_t represents the total labor supply in society that is available for the production sectors in year t.

g). Non-negative constraints

Considering their practical significance, the decision variables should be non-negative.

$$Xt \geq 0, \quad t = 1, 2, 3, \cdots, M \tag{12}$$

2.2. Non-dominated sorting particle swarm optimization algorithm

Traditional algorithms deal with multi-objectives by combining all objectives into a single objective by a weight vector, such as the weighted-sum method (Kim and de Weck, 2005), or selecting one objective to optimize, and giving the other objectives minimal levels below which the solution was deemed infeasible (Jones et al., 2002), such as goal programming (Hanks et al., 2017) and ε-constraint methods (Esmaili et al., 2011). These methods are easy to result in biases in the search process for trade-off solutions, and heavily depend on the shape of the Pareto optimal front (Bui and Alam, 2008). Compared with the traditional algorithms, Multi-Objective Evolutionary Algorithms (MOEAs) are more effective methods to deal with Multi-Objective Problems (MOPs) (Deb, 2014). In the MOEAs, a set of Pareto

optimal solutions can be found in a single simulation run. Among the various MOEAs, the non-dominated sorting particle swarm optimization (NSPSO) algorithm is recognized as one of the most popular and widely used algorithms. NSPSO is a multi-objective optimization techniques based on evolutionary theory and is a modification of the conventional PSO algorithm that is designed to solve multi-objective optimization problems (Li, 2003). Instead of comparing based solely on a particle's personal best with its offspring, as in the conventional single objective PSO algorithm, NSPSO compares all particles' personal best, and these particles' offspring in the entire population. Furthermore, this improved algorithm provides a better method of selecting the better individuals from the entire population, providing the necessary selection pressure to push the population to the Pareto Front (Liu, 2008). Therefore, NSPSO algorithm is applied to solve the proposed multi-objective optimization model.

2.3. Final solutions screening method

Each point of Pareto-optimal front is a trade-off non-inferior solution for satisfying the three objectives under constraint conditions. To facilitate decision-making and to further analyze the change of industrial structure, emissions and employment in realizing the emissions peak, a number of representative solutions need to be selected from the Pareto-optimal front according to the decision preferences of the three objectives. To this end, we applied the multi-criteria tournament decision-gain analysis method (MTD-GAM) (Parreiras and Vasconcelos, 2009) approach to select the solutions of Pareto-optimal front. MTD-GAM is a hybrid method which firstly takes into full account the preferences of the decision makers and then offers the ranking of candidates from best to worst; and then calculates the gains and losses of all possible alternatives on the basis of MTD to obtain the final solution.

2.4. Data and parameters

2.4.1. Data sources

a). The sectoral value-added data are derived from the *China Statistical Yearbook* (NBSC, 2017). The value-added data of sectors in the secondary industry come from the yearbook's table "Main Indicators of State-owned and Non-state-owned Industrial Enterprises above Designated Size by Industrial Sector". For consistency, the annual data are calibrated by the proportion method and the interpolation method (Chen, 2011). The value-added data of the primary industry, the construction industry and the six sectors in the tertiary industry are from the table "Gross Domestic Product". All sectorial value-added data are transformed into 2012 constant price.

b). Sectoral primary energy consumption data are derived from *China Energy Statistical Yearbook* (2010–2017). The energy consumption of coal, crude oil and natural gas are directly quoted from "Consumption of Coal (Crude Oil, Natural Gas, and Electricity) and Its Main Varieties by Sector". The primary electricity consumption is calculated based on the total electricity consumption and the ratio of primary electricity consumption to the total.

c). The number of sectoral employees is derived from "Employment in the Sub-sectors" in *China Statistical Yearbook* [6] over the years of 2006 to 2017.

d). The carbon emission coefficients of coal, oil and natural gas are borrowed from Liu et al.'s (2015b) study. In general, the CO_2 emission coefficient of electricity relies on electricity generation mix and coal consumption of per unit coal-fired electricity generation, which is not fixed (Ang and Su, 2016). However, four types of energy considered in our study are all primary energy. The considered electricity consumption just refers to the hydro power, nuclear power and other primary electricity such as wind and PV power. Thus, the carbon emission coefficient for electricity in our study is considered to be zero.

2.4.2. Data calibration and parameters setting

Different methods are applied to update the data and set parameters according to their characteristics.

a). Trend extrapolation forecast based on the latest historical data. The data updated by this method includes the consumption of coal, oil, natural gas and primary clean electricity of per unit sectorial added value ($(C_k)_t$), labor force required by the unit added value (L_t), the maximum labor force (B_t), final consumption (Y_{1t}), and net exports (Y_{2t}). With the improvement of technology and the decarburization of China's energy consumption structure, the consumption of coal and the labor force required of per unit sectorial added value will generally fall while the consumption of natural gas and primary clean electricity will rise from 2017 to 2030. As the Chinese economy grows the final consumption and net exports will rise.

b). Calibration according to the existing methods. The 'RAS' method (also known as a 'biproportional' matrix balancing technique) (Toh, 1998) is applied to update the technical coefficients (A_t). The structural coefficients relation method, which combines the static and dynamic input-output models (Li, 2009), is used to adjust the investment coefficients (Q_t).the upper limits (φ_1) and lower limits (φ_2) of the sectoral output growth rate are borrowed from the setting of Dong's (2009), who estimated these two values according to the varied range of the values compared to the previous year.

c). Setting based on mandatory targets in energy saving and emission reduction policies of China. The documents of *The Thirteenth Five-Year Plan for Controlling Greenhouse Gas Emissions* states that China's total energy consumption should be controlled within 5.0 billion tce in 2020. While according to the policy of *the Revolution Strategy for Energy Production and Consumption* (*2016–2030*), the upper limit of China's energy consumption in 2030 is 6.0 million. However, due to inconsistent data statistics, industrial sectors' energy consumption is calculated based on the input-output table of 2012 (the latest available data) is 8.6% higher than that based on the *China Energy Statistics Yearbook*. Thus, the maximum energy consumption in 2020 and 2030 is set to 5.2 and 6.3 billion tce. The document of the *Coal Mine Energy Conservation and Emission Reduction Upgrade and Transformation Action Plan* (*2014–2020*) (regarded as Action Plan) states that the proportion of coal in primary energy consumption strives to fall below 62%. Thus, we follow this setting of coal share (α_t).

Details about the model parameters and methods for determining values are given in the Table 1. Prediction equations of $(C_k)_t$ and L_t of each sector are shown in the Table S1–S5 as Supporting Materials.

3. Results and analysis

3.1. Pareto-optimal curve and selected final solution

With NSPSO evolutionary algorithm, the study applies the commonly-used "Center distance (CD)" and "Spacing (S)" to measure the convergence and uniformity of the algorithm. With the same data and parameter settings listed in Table A2, 100 times independent runs are conducted. And the statistical information of the center distance and spacing metrics are shown in Table A3.

We take the run of the values that best approximates the average value of *CD* and *S* as an example to show how the evaluation changes with generations. According to the proposed model, 100 groups of non-inferior solutions of the 3D scatter plot are depicted in the target space, shown in Fig.1. In the planning period (2013−2030), data about the cumulative value of 32 sectors' carbon emissions, GDP (2012 constant price, the same below) and the employees are 191.8–

Table 1
Model parameters and methods for determining values for 2017–2030.

Parameters	Methods for determining values
$(C_k)_t$	Most of their values have been estimated by the trend extrapolation models for each sector according to the recent five-year values (2012–2016). Some values are estimated by moving average method.
L_t	Their values have been estimated by the trend extrapolation models according to the 2005–2015 time series. The simulation maximum relative error is 5% for historical data.
B_t	Their values have been predicted by establishing a logarithmic trend extrapolation model according to the time series (2011–2015) with the equation $y_t = 3508.4 \ln(t) + 71945$ and $R^2 = 0.9248$.
Y_{1t}	The values have been predicted by an autoregressive integrated moving average (ARIMA) model, which is established according to historical data from 2005 to 2012. The equation is $y_t = 999.75 - 0.062y_{t-1} - 0.1087\varepsilon_t + 0.992\varepsilon_{t-1}$. The simulated maximum relative error of the historical data is less than 1.6%, and the minimum $R^2 = 0.998$.
Y_{2t}	Their values have been predicted by an ARIMA similar to Y_{1t}. The equation is $y_t = 231.67 - 0.062y_{t-1} - 0.113\varepsilon_t + 0.992\varepsilon_{t-1}$. The simulated maximum relative error of the historical data is less than 2%, and the minimum $R^2 = 0.968$.
A_t	Their values for 2013–2030 have been refined by the RAS method (Toh, 1998).
Q_t	Estimated by the structural coefficients relation method (Li, 2009).
α_t	The values are set as 62% in 2020 and 56% in 2030, according to the document *Energy Plan for Energy Conservation and Emission Reduction of Coal-power in China (2014–2020)*. The data for the other years are calculated with the interpolation method. The values for the other years are estimated with the interpolation method.
E_t	Their values have been determined by referring to the document *Revolution Strategy for Energy Production and Consumption (2016–2030)* and Yu et al.'s (2012) prediction for China's energy for the maximum supply amount by subtracting residential energy consumption during the years 2013–2030.
φ_1, φ_2	$\varphi_1 = 1.2$, $\varphi_2 = 0.8$. According to the setting of Dong's (2009) study.
r_t	r_t represents the minimum growth rate of GDP. The values are 7% in 2013 and 2014, 6.5% in 2015–2017, 6.0% in 2017–2020, 5.3% in 2021–2025, and 5% in 2026–2030.

194.3 (Gt), 1.85×10^6–1.89×10^6 billion (Yuan), and 14.0–14.3 billion (person).

According to the three objectives of the model, the minimum cumulative value of carbon emissions, the maximum cumulative value of GDP, the maximum cumulative value of employees and the minimum deviation of input-output balance, we set up the preference criteria set $[f_1, f_2, f_3, f_4]$, and set such four preferences as low carbon preference A, economic preference B, employment preference C and equality preference D. The preference information provided by the decision maker is converted into the weights of the criteria with the method of multiplicative preference relations (Zhang et al., 2004), and the results are shown in Table 2. As shown in Table 2, preference B is the same as preference C, indicating that the results are consistent regardless of economic objectives or the employment objectives in the first place. The final solutions are three types of low-carbon preference A, economic preference B and the equality preference D. According to the MTD-GAM method, the solutions of the above three preferences in the three-dimensional objective space are marked in Fig. 1.

3.2. The realization of the carbon emissions peak

Via industrial structure adjustment, China's carbon emissions peak will be realized from 2022 to 2025, and the peak value of CO_2 emissions will range from 11.21 to 11.56 Gt. According to the optimized results (10,000 Pareto solutions) of the proposed multi-objective model, we estimate the carbon emissions from 2013 to 2030, which correspond to the 10,000 Pareto solutions shown in Fig. 2. The solutions also indicate that China could maintain an average growth of approximately 6.1 to 6.4% yr^{-1} for GDP and approximately 0.24% to 0.51% yr^{-1} for employment during the period2013–2030.

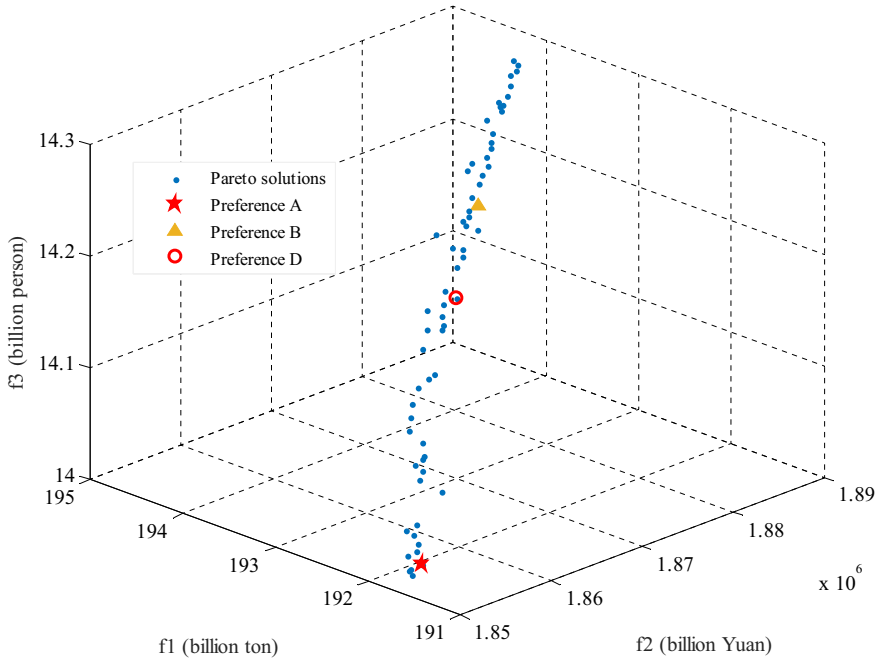

Fig. 1. Pareto-optimal curve and selected final solutions.

Table 2
Solution sets with different decision Preferences.

Preferences	Description	Criteria ranking[a]	Weights	f_1 (Gt)	f_2 (Billion Yuan)	f_3 (Billion person)
A	Low carbon priority	$(f_4 \approx f_1 \succ f_2 \approx f_3)$	(0.338,0.162, 0.162,0.338)	191.8	1.85×10^6	14.0
B	GDP priority	$(f_4 \approx f_2 \succ f_1 \approx f_3)$	(0.162,0.338, 0.162,0.338)	193.6	1.88×10^6	14.2
C	Employment priority	$(f_4 \approx f_3 \succ f_1 \approx f_2)$	(0.162,0.162, 0.338,0.338)	193.6	1.88×10^6	14.2
D	Equal important of all objectives	$(f_4 \approx f_1 \approx f_2 \approx f_3)$	(0.250,0.250, 0.250,0.250)	193.2	1.87×10^6	14.1

[a] Given that $f_1 \succ f_2$ represents that f_1 is strictly more important than f_2, and $f_1 \approx f_2$ means that f_1 is as important as f_2.

Based on the frequency statistics of 10,000 solutions (Fig. A1), emissions are most likely to peak in 2023 (with a frequency of 60.1%), and the average CO_2 peak value is 11.47 Gt. Additionally, the average peak value in each year grows progressively, from 11.38 Gt in 2022 to 11.53 Gt in 2025, which reveals that the sooner the carbon emissions peak, the lower the value will be, and vice versa.

As shown in Fig. 2, China's carbon emissions fell in 2015 and 2016 compared with that in 2014. This is mainly due to: China's economic growth slowed after 2013; coal consumption has declined continuously for three years; the proportion of non-fossil fuel power generation increased from 24.2% in 2014 to 28.2% in 2016. But China's carbon emissions did not really peak in 2014. den Elzen et al. (2016), Korsbakken et al. (2016) also holed the same view. After 2017, with the continued growth of economy and the completion of coal production capacity adjustment, China's carbon mission will keep growing. However, the growth rates are lower than that without the industrial structure adjustment. As a result, the average growth rate of CO_2 emission drops from 7.8% yr^{-1} in 2005–2012 to 0.8%–1.0% yr^{-1} between 2017 and the peak year. The emission between the peak year and 2030 will decline slowly with an annual average drop rate of 0.7%–1.0%.

In the Fig.2, only emissions from fuel combustion (includes sectors' and residents' emissions), regardless of the emissions from cement production and land use.

The peak year is earlier than the study of (Mi et al., 2017). The main reasons are follows. First, the present paper explores the carbon emission peak from the perspective of industrial structure optimization while Mi et al.'s study focuses on scenario analysis of socio-economic system. Second, three objectives are considered simultaneously while only one objective in Mi et al.'s study. Finally, we used the latest data (Updated to 2016) while Mi et al.'s data before 2014.

To further investigate the reasons for the trajectory peak depicted in Fig. 2, we apply the log-mean Divisia index (LMDI) method belonging to the IDA method (Ang and Liu, 2001; Xu and Ang, 2013) to decompose the carbon emission-driving four factors according to the IPAT model (Wang et al., 2017), which are economic scale expansion (*GDP*), industrial structure (*IS*), technological progress (regarded as energy consumption intensity) (*EI*) and energy structure (*ES*).

The decomposition results are shown in Fig. 3**.** It indicates that *IS* is the most important contribution for total emissions going down. To facilitate decision-making and to further analyze the change, three representative solutions, named preference A, B, and D, are selected from the Pareto-optimal front according to the decision preferences of objectives. Taking preference D as an example, emissions in 2023 increase by 1.39 Gt CO_2 compared to 2012, and GDP expansion results in a 7.46 Gt increase in emissions, with a contribution rate of 538.2%. The contribution rates of technological progress and industrial structure to emissions growth are −276.1% and −102.2%, respectively. After the peak is reached, China's industrial carbon emissions decreases by 0.68 Gt in 2030 compared to 2023. *IS*, with a contribution rate of 428.4%, constitutes the most important factor for emission reduction.

3.3. Structural changes in the sectors' output and carbon emissions

China's economy experiences structural change whereby the leading industry changes from secondary industry to tertiary industry. Regarding value-added, the secondary industry's value decreases from 45.5% in

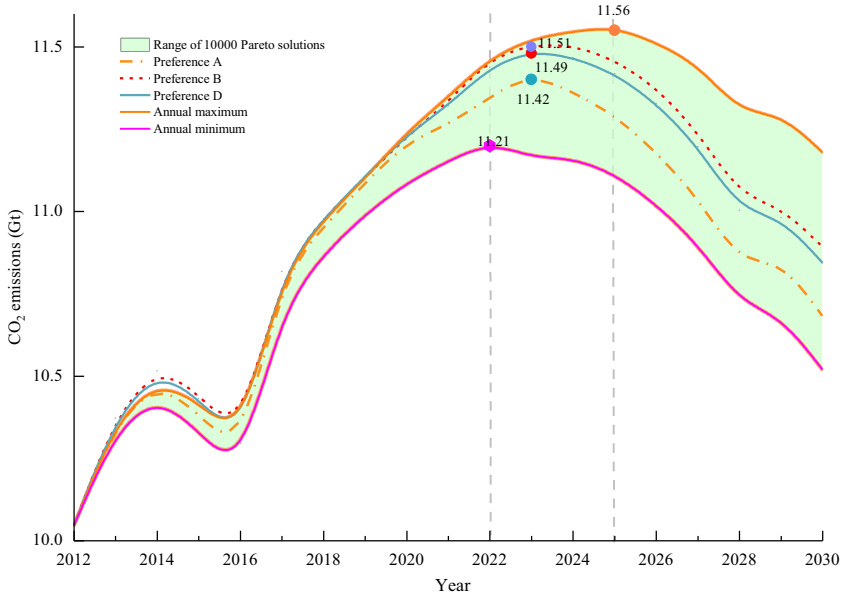

Fig. 2. Energy-related CO_2 emissions trajectory.

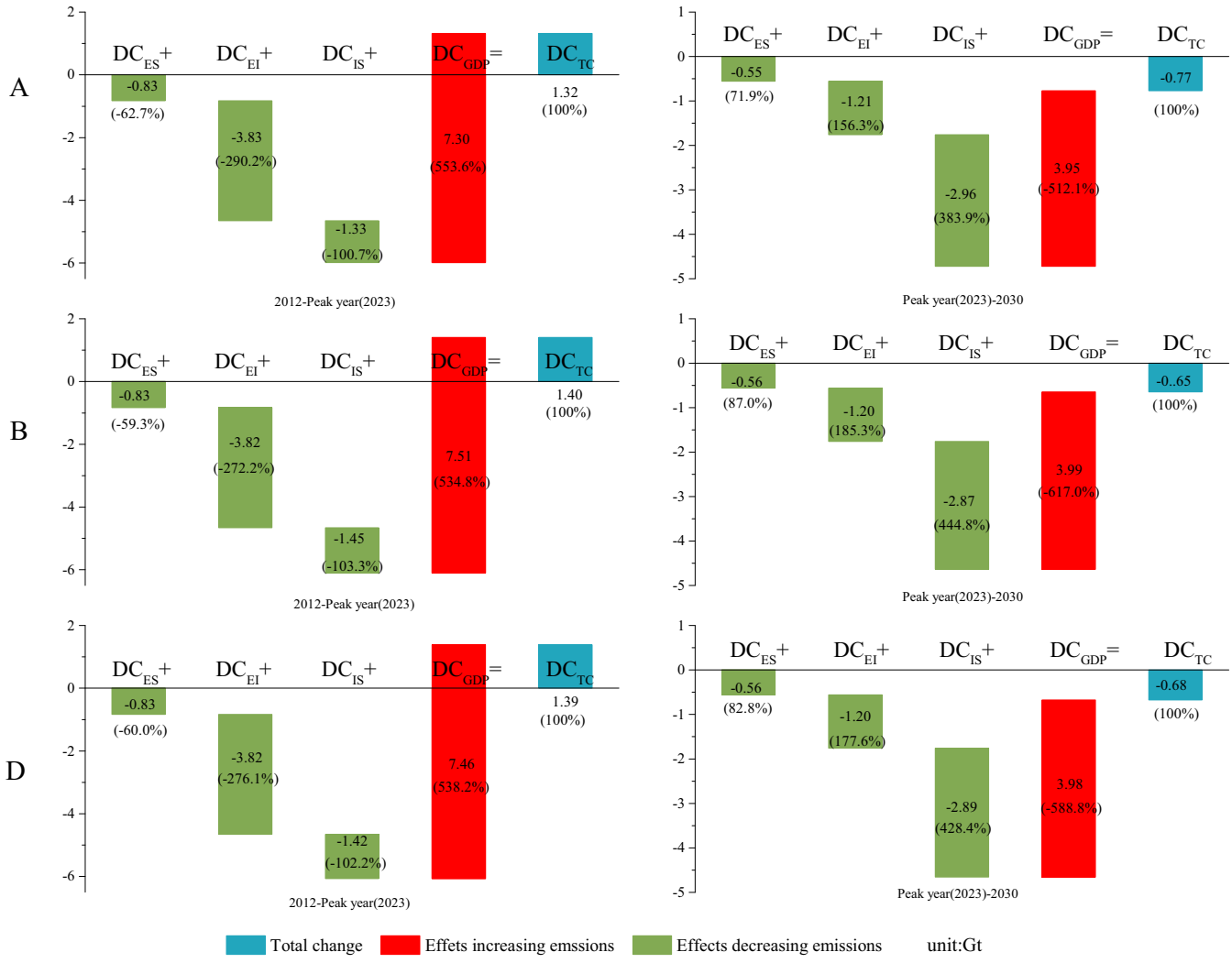

Fig. 3. Decomposition of carbon emission-driving factors before and after the peak.

2012 to approximately 42.3% in the peak year and further to 34.8% in 2030, while that in the tertiary industry increases from 44.8% in 2012 to approximately 49.2% in the peak year and then to over 56.0% in 2030, as shown in Fig. 4(a). Such changes are mainly attributed to the differentiated growth rate of the value added of the second and tertiary industries in 2013–2030. That is, the prior situation, in which the value added of the second industry grew higher than that of tertiary, changes into a new pattern, where the value added of the tertiary industry exceeds that of the secondary industry. For instance, the average growth rate of the second industry's value added decreases from 11.8% yr^{-1} in 2006–2012 to 6.1% yr^{-1} during 2013 and the peak year (2023), and it further decreases to 2.5% yr^{-1} in 2023–2030. Within the tertiary industry, the value added grows at a rate of 7.6% yr^{-1} from 2013 to 2022 and maintains a high rate of 7.5% in 2023–2030, as shown in Fig. 4(b). The reasons for this difference in growth rate are twofold. First, to minimize carbon emission, the output growth of sectors with high carbon emissions in the secondary industry will be subject to different degrees of restriction, according to the proposed multi-objective model. Second, to maintain a high GDP growth rate, the tertiary industry must keep growing at a high rate when the second industry is restricted and the first industry is stabilized.

Most sectors' emissions in the secondary industry undergo different degrees of decreases from 2013 to 2030 after China's industrial restructuring, while emissions of the tertiary industry generally increase. Furthermore, the sectors' increase in emissions and their growth magnitude are smaller after the peak-reached year than before the peak-unreached year. Take preference D as an example: compared with 2012, carbon emission increases in 17 sectors in the peak year (2023), with an average growth rate as high as 50.3%, shown in Fig. 5. Among these 17 sectors, 5 sectors within the tertiary industry increase their emissions, with an average rate of 58.1%. In the same period, 14 sectors within the second industry and one (S30) in the service industry decrease their emissions, with an average rate of 22.4%. However, during the period of the peak year to 2030, 17 sectors' emissions grow, with an average rate of 32.2%. The emissions of 15 sectors (13 in the second industry and two (S30, S31) in the service industry) decrease at an average rate of 22.0%.

The sectors of energy processing and conversion (S11 and S23) are the major emission sources both before and after the peak is reached. The CO_2 emissions shares of these two sectors account for more than 54.0% of the total emissions from 2012 to 2030 (Fig. 6). This high proportion is determined by the production characteristics of the two sectors, which transfer high carbon-emitting fuels (such as raw coal and crude oil) into low-carbon fuels (such as liquefied petroleum gas) or carbon-free electricity and heating power. These two sectors undertake transferred carbon emissions from other sectors (such as the transportation services sector).

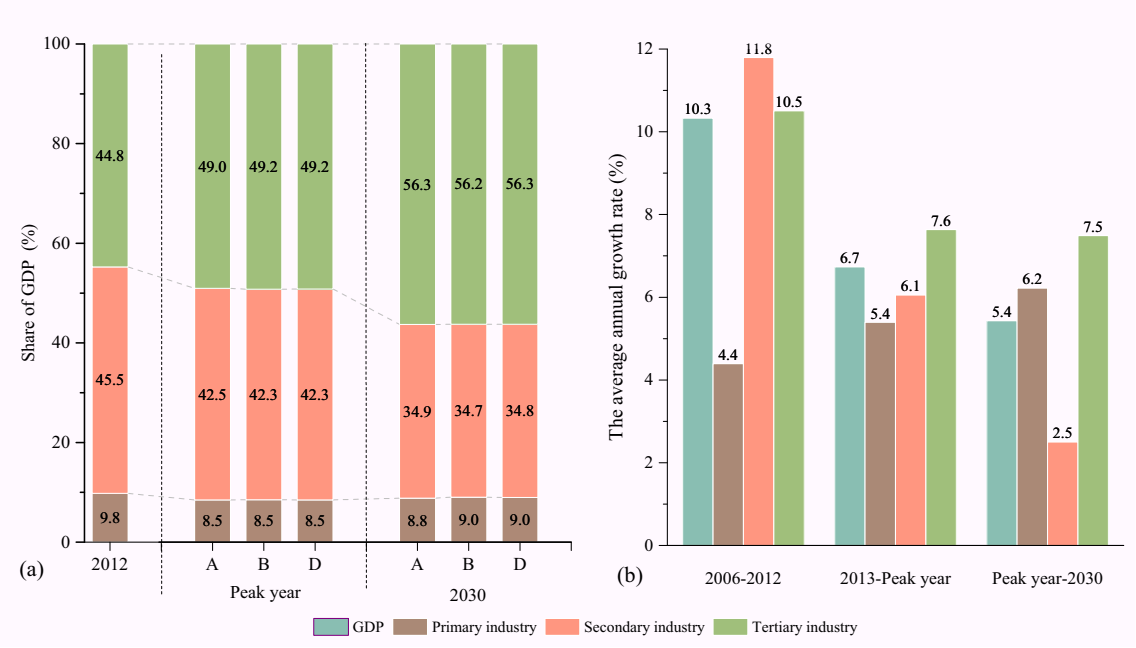

Fig. 4. The composition of three industries' value added and annual growth rates.
The rate refers to the three preferences.

Emissions proportions from heavy manufacture sectors S12, S13 and S14 decline between 2013 and 2030. For example, in preference D (Fig. 6), the emissions proportion of the three sectors drops from 21.9% in 2012 to 15.6% in the peak year, and it further decreases to 11.2% in 2030. The proportions fall mainly because the output growth of these three carbon-intensive sectors is restricted and their energy consumption is cut in industrial restructuring, according to our proposed multi-objective model. These changes are consistent with China's ongoing industrial policy of "reducing overcapacity and adjusting economic structure".

3.4. Energy consumption and its mix in the peaking process

The energy consumption of China's 32 economic sectors will respectively peak in 2025, 2026, and 2026 with 5.42, 5.52, and 5.50 billion tce in preference A, B and D. According to the optimized industrial structure

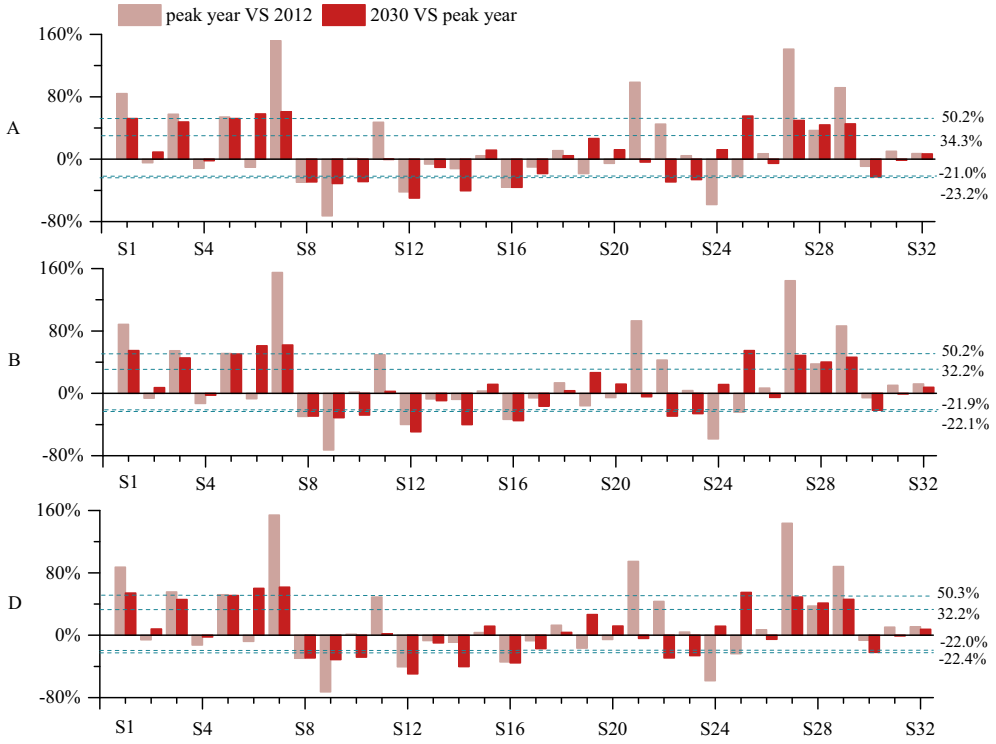

Fig. 5. Sectors' CO_2 emission changes.

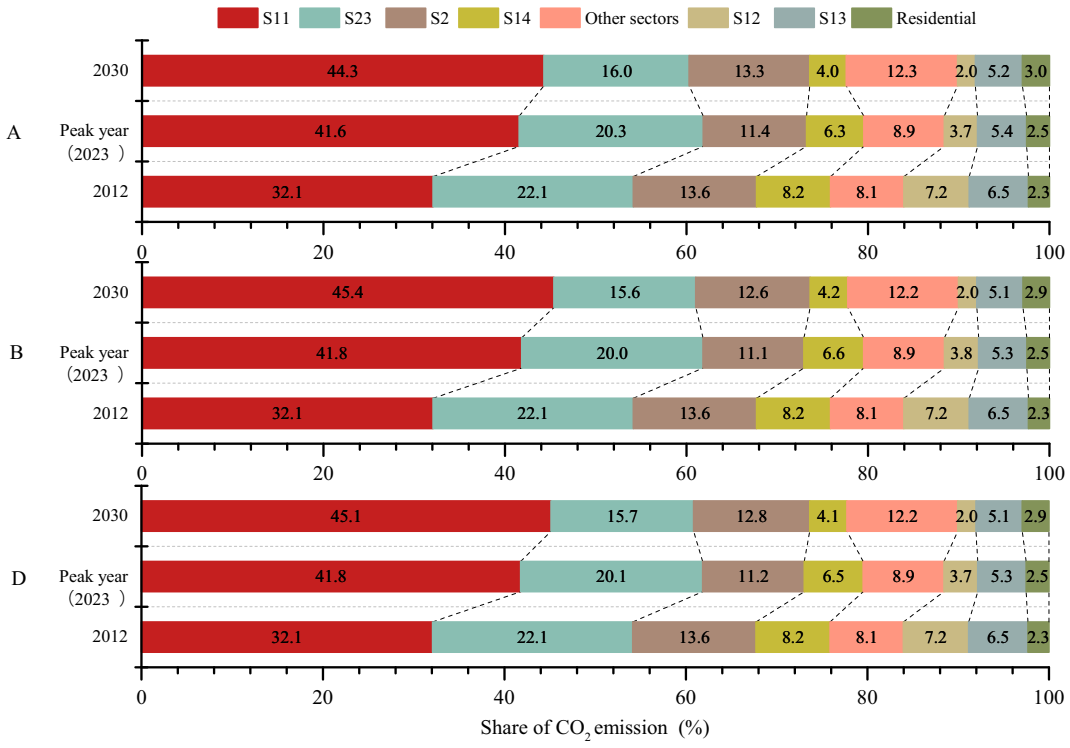

Fig. 6. CO_2 emission shares of sectors.

adjustment trajectory from 2013 to 2030, China's coal consumption has peaked in 2013. The consumption trend of coal, oil, natural gas and clean electricity are shown in Fig. 7. It shows that China's coal consumption peaked in 2013 except a rebound in 2017. Although coal consumption is at a high plateau during 2018–2021, it still does not exceed the consumption in 2013. From the year of 2022, China's coal will continue to decline steadily. Oil consumption will peak around 2023 to 2025 in three preferences. Before peaking, oil consumption still has an average annual growth of 2.9%. This may because of the substitution of oil for coal and demand growth from the increase of resident's cars. Different with coal and oil, consumption of natural gas and primary electricity in China continue to grow rapidly. The average annual growth rates of natural gas consumption and primary electricity are 8.8% and 6.4% between 2013 and 2030, respectively.

In three preferences, the share of coal consumption in primary energy consumption declines from 67% in 2012 to 54.0%–54.2% in the peak year (down an average 19.2%), as shown in Table 3. The fastest growth appears in natural gas consumption, from 3.6% in 2012 to approximate 7.6% in the peak year and further to 12.5%–13.3% in 2030. Compared to that in 2012, the proportion of non-carbon primary electricity consumption increases by 94.5% in the peak year and by 146.4% in 2030. The proportion of crude oil is fixed between 24.8% and 25.8%. The reason for this change in energy structure is as follows. Although the Chinese government has been working to reduce the proportion of high-carbon coal in the past decade and has set explicit constrained targets, the proportion of coal consumption in 2030 fails to fall below 45% as a result of China's coal-based energy resource endowment and the energy demand for economic growth. Aided by related policies and more mature power generation technologies, primarily clean power (such as hydropower, wind power and photovoltaic) as a carbon-free energy will develop rapidly in 2013–2030. However, limited by resource development potential, it will not exceed the proportion of oil consumption to become the second energy consumption source.

3.5. Changes in employment in the peaking process

The sectors in the tertiary industry play a crucial role in ensuring China's future employment security. The number of employed persons increases from 767.0 million persons in 2012 to 812.4–825.8 million persons in 2030. During the 2013–2030 periods, the average annual growth rate of employment is 0.32%, 0.39%, and 0.41% in preferences of A, B, and D. Among 32 economic sectors, service sectors such as wholesale and retail trade (S28) and hotels and catering (S29) are the main sectors for employment growth, while agriculture remains the sector with most transferred labor force. Employment changes of sectors are shown in Fig. 8. For example, in preference D, the employment of S28 and S29 increases from 5.2% in 2012 to 12.2% in the peak year and then to 19.8% in 2030, while that of the agriculture sector declines from 33.6% in 2012 to 21.3% in 2023 and then to 17.0% in 2030. This is mainly due to the less strict requirements for job skills and educational level in S28 and S29, which, with flexible and diverse forms of employment, are able to absorb a large number of less-educated migrant workers from the agriculture sector. The proportion of employment in the heavy and chemical industries decline slightly from 16.4% in 2012 to 16.1% in 2030, while that in the light industry increases from 8.3% in 2012 to 10.1% in the peak year and down to 9.3% in 2030.

4. Discussion and policy recommendation

Restructuring the energy-intensive based industrial structure is now an important policy for China to spur its economic growth, employment security and poverty elimination. However, we shed new light on industrial restructuring with respect to the carbon emissions peak. These optimized industrial structural changes are an important strategy for China to achieve its carbon emissions peak. If the industrial structure and energy intensity evolve in a business-as-usual fashion (i.e., in keeping with the historical trend of 2005–2012), China will not be able to

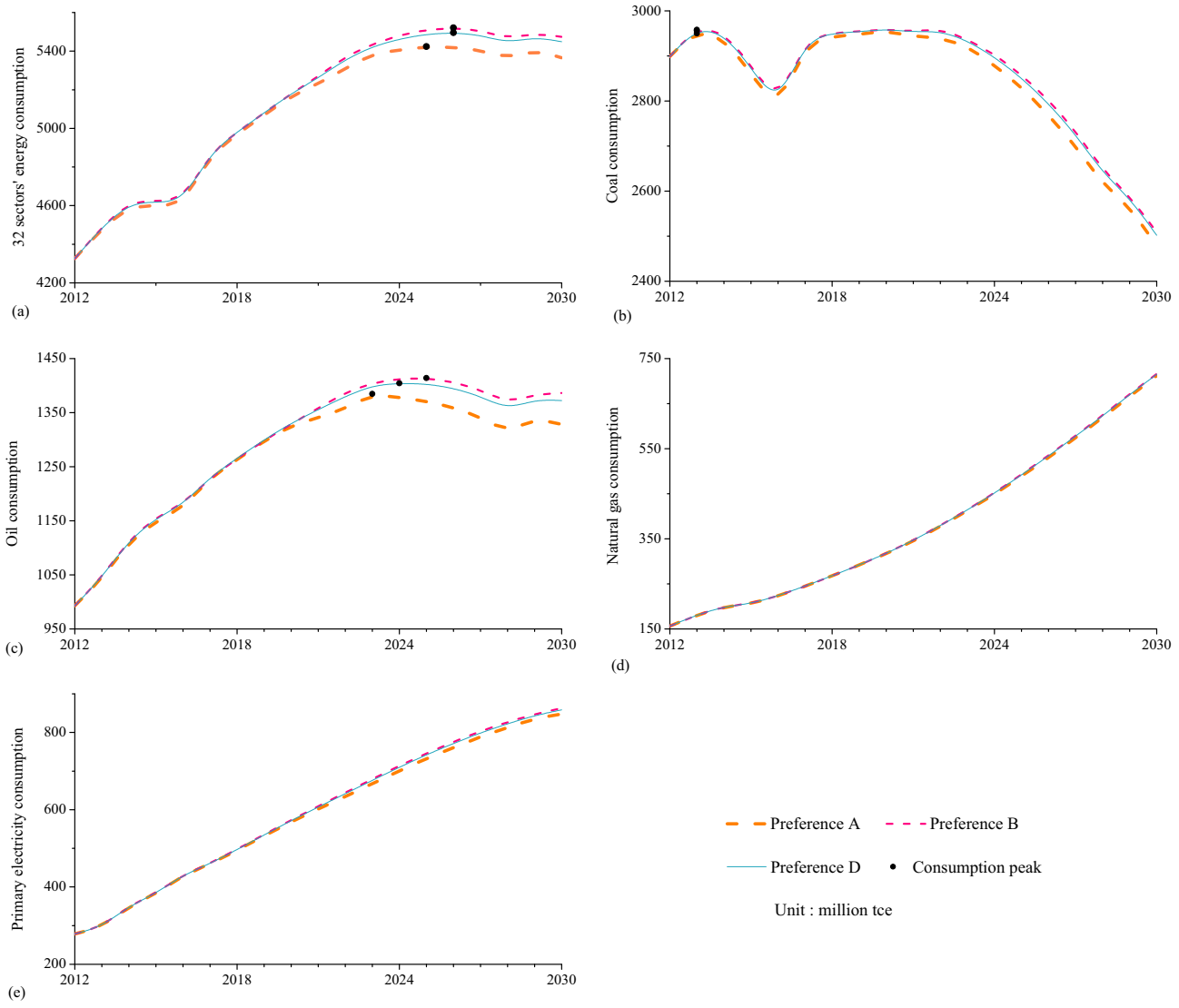

Fig. 7. Consumption of primary energy sources (2012–2030).

achieve the peak by 2030 at different GDP growth rates (as depicted in Fig. A2).

For China's carbon emissions to peak, the output growth of carbon-intensive and low-technology sectors (such as sector S12 and sector S14) should be limited, but the output of the high-technology and high-value-added sectors (such as sector S29 and sector S30) should increase. The elimination of growth-limited sectors' overcapacity affects many local regions' interests, such as GDP growth, taxes and employment. As a result, the central government's industrial restructuring policies are rejected by some local governments for fear of harming their regional economic growth and employment security. To achieve a triple-win situation in terms of the carbon emission peak, GDP growth and employment security, a new constraint economic-carbon emission-employment optimization model is proposed. According to the optimized results of the model, China's energy-related carbon emissions could peak before 2025 with GDP growth of 6.1–6.4% yr^{-1} and employment growth of 0.24–0.51% yr^{-1} during the 2013–2030 period according to 10,000 Pareto solutions. These findings may eliminate many concerns among local governments that carbon reduction may be harmful to their local economy and employment.

Table 3
Primary energy consumption mix.

Fuels shares (%)	2012	A		B		D		Average growth rates of A, B and D (%)		
		Peak year	2030	Peak year	2030	Peak year	2030	2012-peak year	Peak year-2030	2012-2030
Coal	67.0	54.2(2013*)	46.2	54.0 (2013)	45.8	54.1(2013)	45.9	−19.2	−15.0	−31.4
Crude oil	23.0	25.7(2023)	24.8	25.8 (2025)	25.3	25.8(2024)	25.2	12.1	−2.7	9.1
Natural gas	3.6	7.7	13.3	7.6	12.5	7.6	13.1	112.1	72.3	265.5
Primary electricity	6.4	12.4	15.8	13.1	15.8	13.1	15.8	94.5	26.7	146.4

* Indicates peak year of the fuel.

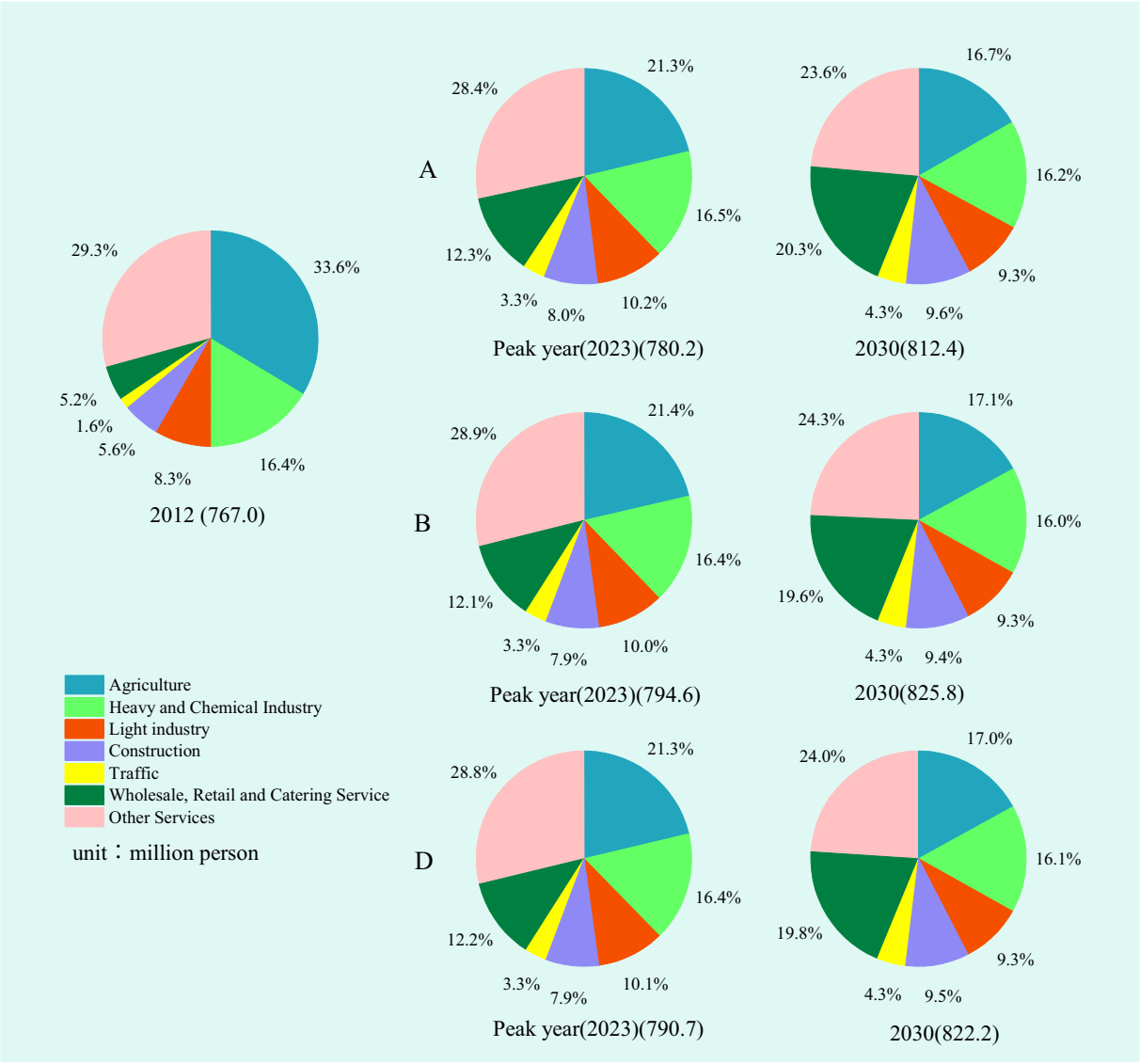

Fig. 8. Shares of sectors' employment changes.

To peak emission before 2025, the Chinese government should guide the investment structure to regulate the sector's output. The scale and structure of the investment determine the sectorial output capacity, which directly affects the direction of economic structure changes and the volume of carbon emission. Therefore, a unified national market system must be implemented to eliminate local protectionism and to prevent reduplicate investment. In our study, a guideline (shown in Table A4 to Table A6) for the sectoral capital investment has been estimated. The results can provide useful information on the formulation of investment policies for Chinese central and local governments. They can also support the decision-making for various investors. Furthermore, the changes in sectorial output from 2013 to 2030 can provide a clear roadmap to peak emission by industrial reconstructing.

China should continue to maintain the decline in energy intensity of the industrial sectors. In the proposed optimization model in this study, the energy intensity of each sector is considered as an exogenous variable, and their values for 2017–2030 are predicted based on historical data. The energy intensity of all sectors is generally declining. Therefore, it is should maintain the existing policies for energy conservation and emission reduction and maintain the existing downward trend of energy intensity, especially the electric and heat sector, heavy manufacture sectors and chemical manufacture sector. It is necessary to strengthen the screening, demonstration, and popularization of key energy-saving and emission reduction technology or measures such as integrated gasification combined cycle (IGCC) in power plant.

Increase the effective supply of clean electricity and ensure its effective substitution for oil consumption. Based on the industrial structure optimization and sectors' energy consumption, the peak of oil consumption is the key to the realization of carbon emissions in China when coal consumption has reached a peak in 2013. The peak time for oil consumption is almost synchronized with the peak time for carbon emissions (2022–2025). From 2013 to 2030, the average annual growth rate of renewable electricity and nuclear power in China needs to maintain 6.4%. Therefore, actively developing nuclear power and realizing effective supply of renewable power and its large-scale grid connection are the conditions of ensuring that China's carbon emissions reach the peak.

Acknowledgements

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Appendix A

Table A1
Sector division.

	Sector's code	Sector in present study	Sector in I-O table of 2012
Primary Industry	01	Agriculture	Agriculture, Forestry, Animal Husbandry & Fishery
Secondary Industry	02	Coal Mining	Mining and Washing of Coal
	03	Petroleum Extraction	Extraction of Petroleum and Natural Gas
	04	Metal Ores	Mining and Processing of Metal Ores
	05	Nonmetal Ores	Mining and Processing of Nonmetal Ores and Other Ores
	06	Foods	Manufacture of Foods, Beverage & Tobacco
	07	Textile	Manufacture of Textile
	08	Wearing Apparel	Manufacture of Textile Wearing Apparel, Footwear, Caps, Leather, Fur, Feather (Down) and Its products
	09	Timber and Furniture	Processing of Timber and Furniture
	10	Papermaking	Papermaking, Printing and Manufacture of Articles for Culture, Education and Sports Activities
	11	Petroleum Processing	Processing of Petroleum, Coking and Processing of Nuclear Fuel
	12	Chemical Industry	Chemical Industry
	13	Non-metallic Mineral	Manufacture of Non-metallic Mineral Products
	14	Smelting Metals	Smelting and Pressing of Metals
	15	Metal Products	Manufacture of Metal Products
	16	General Purpose Machinery	Manufacture of General Purpose and Special Purpose Machinery
	17	Transport Equipment	Manufacture of Transport Equipment
	18	Electrical Machinery	Manufacture of Electrical Machinery and Apparatus
	19	Communication,	Manufacture of Communication, Computers and Other Electronic Equipment
	20	Measuring Instrument	Manufacture of Measuring Instrument and Machinery for Cultural Activity and Office Work
	21	Artwork	Manufacture of Artwork, Other Manufacture
	22	Scrap	Scrap and Waste
	23	Electric and Heat	Production and Supply of Electric Power and Heat Power
	24	Gas Production	Production and Distribution of Gas
	25	Water Production	Production and Supply of Water
	26	Construction	Construction
Tertiary Industry	27	Traffic Services	Traffic, Transport and Storage Post Service
	28	Wholesale and Retail	Wholesale Trade and Retail Trade
	29	Hotels and Catering	Hotels and Catering Services
	30	Financial	Financial Intermediation
	31	Real Estate	Real Estate
	32	Other Services	Information Transmission, Computer Service and Software Leasing and Commercial Services Research and Experimental Development Composite Technical Services Management of Water Conservancy, Environment and Public Facilities Services to Households and Other Services Education Health, Social Security and Social Welfare Culture, Sports and Recreation Public Management and Social Organization

Table A2
Parameters and values of the NSPSO algorithm.

Parameter	Description	Value
popsize	The size of the population	100
maxgen	The maximum evaluation generation	1000
u_1, u_2	Cognitive coefficient and social coefficient	0.8
w_{max}, w_{min}	Inertial coefficients of maximum and minimum	1.2; 0.1
V_{max}	The maximum speed for a variable	$V_{max} = 10\,\%$ of variable range

Table A3
The statistical information of the center distance and spacing metrics.

Indicators	Average	Standard deviation	The best	The worst	The biggest	The least
CD	1.95	0.10	–	–	2.29	1.67
S	0.04	0.02	0.01	0.15	–	–

Table A4
The capital formations of each sector (Preference A) (unit: billion yuan, 2012 price).

Sector	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
S1	746.8	854.3	1097.4	1249.9	1422.3	1623.6	1881.6	2410.5	2426.3	2860.6	3590.7	4014.6	5203.0	5872.0	7317.5	8988.9	11,898.7	14,541.8
S2	444.6	467.4	537.8	568.8	622.0	650.7	716.5	798.9	771.8	830.5	917.6	983.9	1076.9	1101.3	1303.5	1403.9	1745.6	1806.5
S3	208.7	207.7	205.0	212.9	248.3	217.7	248.7	259.8	221.6	254.4	344.0	260.6	301.8	318.9	370.9	391.5	682.6	611.5
S4	172.6	184.8	205.3	224.6	227.5	275.6	281.5	350.4	337.7	348.6	480.8	620.6	727.8	709.7	984.1	1161.8	1248.4	1072.1
S5	167.3	178.4	204.7	215.2	260.9	256.3	287.9	308.8	294.4	346.5	361.6	386.6	441.5	459.8	536.1	609.3	677.8	746.6
S6	1161.3	1232.6	1475.1	1563.3	1704.0	1811.5	1987.2	2345.3	2229.4	2411.6	2862.0	2975.7	3594.6	3815.1	4485.2	5109.4	6322.5	7168.8
S7	506.9	590.3	722.6	791.4	897.2	980.2	1131.4	1229.2	1355.2	1564.0	1734.1	2033.6	2301.1	2591.3	3050.2	3557.4	4236.8	4886.3
S8	357.9	404.9	490.6	539.2	608.6	662.1	801.7	833.5	916.1	1018.3	1186.5	1368.1	1542.7	1793.8	2148.8	2434.6	2976.3	3330.6
S9	388.7	445.6	529.1	570.4	615.7	715.7	790.2	895.3	938.2	1043.1	1177.8	1298.3	1478.0	1662.2	1876.2	2211.4	2471.3	2811.8
S10	342.0	372.1	430.4	470.4	520.1	541.0	634.4	701.0	708.4	758.5	882.6	964.3	1121.4	1261.4	1438.7	1595.0	1970.9	2096.2
S11	213.0	219.6	250.5	258.1	296.3	291.3	349.8	359.8	345.1	378.9	464.0	526.2	604.7	638.4	792.9	863.7	1005.7	1128.1
S12	1345.4	1381.8	1695.1	1942.8	2006.2	2046.5	2459.4	2859.4	2653.5	2829.6	3522.8	3986.8	4699.5	5107.2	6481.2	7006.9	9173.3	9816.2
S13	1044.6	1092.8	1366.7	1338.4	1545.6	1733.6	1771.8	2108.2	2176.2	2422.9	2801.6	3049.3	3696.3	4278.8	5041.4	6075.0	7294.7	8088.3
S14	682.2	738.3	836.5	886.5	942.8	1075.8	1139.5	1315.1	1367.5	1415.3	1706.4	1992.1	2339.7	2557.3	3075.0	3632.1	4190.3	4415.7
S15	454.6	512.0	595.6	639.9	714.7	793.2	883.7	1010.5	1063.3	1148.2	1339.4	1484.2	1776.4	2026.8	2381.3	2735.9	3374.1	3740.4
S16	1170.3	1303.9	1522.8	1633.8	1913.4	1985.4	2327.3	2516.1	2689.5	2855.4	3402.4	3845.9	4428.4	5001.1	6010.9	6861.7	8307.1	9160.5
S17	776.3	842.0	913.0	959.1	1078.8	1069.4	1219.1	1214.0	1309.9	1437.3	1605.5	1745.4	1961.2	2158.8	2509.9	2763.8	3162.8	3782.4
S18	654.2	719.2	850.4	914.7	1030.4	1152.9	1283.1	1510.5	1622.3	1688.4	2024.1	2255.5	2804.5	3276.4	3846.4	4422.0	5585.0	6345.7
S19	378.6	397.6	442.3	425.3	460.8	515.4	500.8	550.7	549.6	565.5	632.2	636.4	759.7	761.8	934.6	906.7	1106.8	1230.9
S20	112.2	124.1	138.9	148.4	161.3	170.7	187.9	210.7	215.9	227.1	255.4	268.4	311.0	350.4	397.5	414.2	521.2	551.7
S21	154.6	165.3	190.3	200.6	221.6	228.2	261.3	292.6	290.0	312.0	366.8	379.8	453.4	518.4	595.0	611.8	797.6	840.1
S22	46.3	50.4	56.7	62.8	65.2	78.4	83.0	101.2	101.1	108.1	139.8	176.7	205.9	213.5	279.3	332.8	375.1	362.6
S23	1089.0	1191.4	1412.3	1562.5	1737.9	1882.9	2162.2	2482.7	2521.3	2827.0	3265.5	3700.3	4313.1	4679.6	5797.5	6556.2	8301.8	9172.9
S24	155.3	176.3	208.1	211.7	276.0	285.8	360.3	373.7	397.7	461.8	568.6	676.2	786.4	870.0	1077.4	1254.9	1373.3	1748.1
S25	201.6	229.1	277.0	306.9	354.3	388.1	455.4	543.9	585.1	652.9	796.2	889.6	1086.5	1249.5	1533.8	1758.4	2266.4	2583.6
S26	338.8	330.3	372.2	356.9	376.9	381.4	394.4	407.5	391.7	399.0	438.7	446.4	504.6	544.3	592.6	638.9	726.3	754.9
S27	2783.9	3038.5	3630.6	3869.8	4659.8	4888.3	5933.6	6518.1	6756.2	7676.9	9449.9	10,837.7	13,166.1	14,938.1	18,345.1	21,177.3	26,037.5	30,792.6
S28	813.3	909.7	1115.7	1247.8	1446.9	1591.7	1889.4	2220.6	2324.5	2641.6	3253.3	3700.6	4590.0	5279.9	6561.1	7626.9	9874.7	11,565.4
S29	431.6	455.9	539.4	587.2	703.8	697.3	887.5	949.6	980.9	1083.3	1336.0	1453.4	1810.7	2145.8	2570.1	2770.7	3718.2	4060.0
S30	78.2	70.4	70.7	63.9	64.2	56.9	57.5	52.6	45.8	43.0	43.6	42.0	42.7	40.7	41.6	39.9	41.4	40.0
S31	8555.3	8494.5	10,376.2	11,425.2	14,764.7	14,193.3	19,105.4	19,358.6	20,307.7	22,741.8	27,622.9	32,538.5	39,488.9	46,135.3	55,404.5	63,276.9	79,705.8	89,387.9
S32	5013.5	4979.1	5675.6	5818.1	6509.9	6318.6	7322.7	7658.3	7410.9	7772.3	9012.7	9456.5	11,021.6	12,140.5	13,784.9	14,492.1	17,806.2	18,686.1

Table A5
The capital formations of each sector (Preference B) (unit: billion yuan, 2012 price).

Sector	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
S1	778.5	914.8	1077.5	1179.5	1487.6	1697.0	2030.2	2521.2	2578.3	3267.6	3815.5	4664.8	5718.0	6491.1	7935.4	9791.5	11,894.0	14,481.9
S2	456.5	496.4	546.2	565.5	600.6	658.9	710.7	783.8	788.0	876.6	922.0	1019.8	1073.5	1177.8	1275.9	1394.7	1707.7	1874.2
S3	225.8	211.1	223.5	207.6	219.3	223.7	247.6	267.2	279.5	316.6	307.9	319.3	344.8	357.2	386.1	418.8	635.4	678.1
S4	171.4	192.6	193.5	233.5	246.0	290.0	343.0	370.9	415.0	478.9	496.6	607.1	674.4	833.2	944.7	1057.9	1282.2	1539.4
S5	166.5	185.6	204.4	221.4	231.8	253.0	280.1	312.0	309.2	345.6	360.6	406.4	439.6	483.3	535.2	598.5	671.2	772.4
S6	1198.0	1300.3	1456.5	1510.3	1756.3	1891.9	2102.3	2437.4	2292.5	2759.7	2994.0	3472.0	3952.2	4165.0	4753.8	5497.5	6239.8	7202.1
S7	519.6	615.2	685.3	768.4	881.0	983.3	1178.5	1258.8	1409.9	1579.3	1841.6	2054.2	2259.6	2778.9	3202.4	3654.0	4375.9	4931.5
S8	361.6	414.0	480.1	553.3	626.2	678.8	801.9	845.7	918.3	1090.1	1260.8	1478.3	1523.0	1846.6	2170.0	2488.2	2982.8	3497.1
S9	382.7	453.4	507.0	558.7	647.5	716.8	801.0	870.0	958.5	1052.0	1172.4	1354.9	1516.4	1619.5	1925.8	2123.3	2495.1	2836.7
S10	356.1	383.6	435.1	474.1	529.8	571.9	620.7	706.7	733.7	843.3	954.5	1055.2	1141.5	1288.9	1524.2	1685.3	1944.8	2279.5
S11	212.3	226.3	252.4	260.4	292.8	314.8	343.1	380.4	391.8	432.1	492.1	572.3	613.4	670.0	768.9	880.4	1012.8	1229.1
S12	1373.0	1522.6	1754.5	1762.4	2065.9	2280.1	2459.0	2858.6	2904.4	3449.9	3835.9	4607.9	4961.3	5551.4	6604.7	7460.8	8822.4	10,522.3
S13	1051.0	1123.6	1232.1	1375.2	1593.2	1696.2	1881.3	2075.5	2169.6	2540.0	2779.0	3378.1	3812.7	4028.6	5034.6	6006.8	7081.5	8707.1
S14	683.3	747.6	799.9	890.6	999.0	1105.7	1244.4	1378.4	1483.5	1667.1	1786.6	2103.6	2369.3	2649.2	3139.4	3574.3	4148.5	4926.4
S15	460.9	515.7	580.7	634.2	743.1	805.8	900.8	1029.3	1087.5	1260.3	1394.6	1643.0	1808.1	2010.7	2442.8	2815.1	3256.1	3918.5
S16	1211.0	1358.1	1507.7	1677.9	1886.2	2110.4	2403.5	2752.0	2962.4	3242.8	3553.5	4175.7	4744.7	5271.1	6219.7	7281.8	8206.1	9873.9
S17	800.4	838.7	953.7	994.4	1101.0	1198.0	1303.0	1440.1	1440.9	1522.7	1773.8	1975.8	2177.6	2376.5	2713.8	2928.2	3502.3	3819.3
S18	665.4	743.1	850.9	933.2	1075.6	1197.8	1319.4	1566.1	1655.7	1940.5	2172.6	2566.0	2875.9	3222.9	3965.6	4583.8	5398.3	6516.4
S19	399.8	424.1	427.3	483.9	490.2	547.1	525.2	606.7	566.4	650.2	643.2	747.3	743.3	862.2	869.4	1026.8	1080.2	1212.8
S20	117.6	128.5	142.8	152.1	166.5	175.6	189.7	213.8	218.7	248.1	272.9	304.3	318.7	346.9	404.6	442.7	501.4	580.6
S21	160.8	173.2	194.2	208.7	229.8	242.7	258.6	296.8	295.4	350.9	394.5	444.7	443.8	501.5	602.2	665.8	771.7	919.0
S22	46.1	52.0	53.8	64.2	69.2	81.3	94.9	104.9	117.8	135.9	146.0	174.6	198.3	241.4	278.4	317.5	383.4	460.0
S23	1110.0	1264.3	1436.1	1528.3	1727.0	1917.1	2183.9	2498.1	2614.7	3018.5	3376.8	3950.1	4386.8	5022.9	5783.7	6737.9	8113.8	9587.2
S24	153.5	171.5	204.7	223.5	267.5	295.6	343.7	402.9	425.2	481.2	579.2	683.9	793.0	887.0	1032.0	1246.5	1425.6	1766.7
S25	206.2	235.6	277.0	307.2	359.9	400.6	458.6	550.4	590.8	713.1	820.9	983.4	1110.2	1275.1	1552.9	1823.9	2202.4	2693.9
S26	348.2	334.5	357.7	359.5	396.5	388.9	397.1	417.4	393.5	427.1	452.2	500.6	512.4	513.4	595.7	652.2	707.8	814.7
S27	2794.7	3106.7	3601.9	3976.5	4676.6	5203.1	5909.5	6888.1	7261.5	8474.2	9979.8	11,932.6	13,462.1	15,265.8	18,439.8	21,956.0	26,064.0	32,251.8
S28	831.3	951.0	1109.2	1249.7	1482.1	1687.4	1939.2	2308.7	2425.6	2959.3	3433.0	4170.2	4750.4	5542.0	6730.2	8068.0	9759.4	11,935.3
S29	443.2	476.5	566.1	619.3	716.6	764.9	852.7	1026.9	1025.8	1233.3	1467.7	1706.6	1830.5	2106.0	2630.4	3042.0	3567.5	4528.4
S30	79.5	72.3	71.4	65.7	64.3	59.8	56.7	55.7	48.2	47.1	46.1	45.9	43.0	41.3	41.8	41.3	41.0	42.5
S31	8533.1	8891.7	10,943.3	12,141.5	14,256.3	15,658.7	18,049.7	21,551.1	21,009.3	24,577.1	29,743.3	34,852.2	39,885.9	46,386.6	56,190.7	66,006.0	77,052.8	97,519.7
S32	5118.5	5212.6	5794.0	6039.5	6637.8	6844.9	7216.6	8080.5	7685.7	8736.9	9636.4	10,782.6	11,135.0	12,018.9	13,986.3	15,429.8	17,221.3	20,272.3

Table A6
The capital formations of each sector (Preference D) (unit: billion yuan, 2012 price).

Sector	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
S1	771.8	893.5	1083.7	1197.6	1467.0	1676.6	1987.4	2480.6	2541.6	3160.2	3736.5	4480.9	5539.6	6322.4	7771.4	9563.7	11,914.5	14,513.6
S2	454.4	486.4	545.0	566.7	607.5	658.1	711.9	787.7	784.8	864.3	919.3	1006.2	1076.5	1157.6	1285.0	1398.5	1718.7	1857.6
S3	223.0	208.2	220.1	210.8	229.4	222.9	248.6	268.1	261.5	296.5	318.3	302.9	332.4	348.4	385.2	414.6	647.7	658.2
S4	171.7	189.7	197.4	230.6	241.3	286.6	325.9	365.1	391.7	439.2	491.6	609.6	690.5	795.8	951.3	1087.2	1272.5	1413.1
S5	167.0	184.1	204.4	219.0	240.2	254.4	282.8	310.8	305.4	346.0	362.0	399.8	440.8	476.5	535.6	602.2	673.4	765.7
S6	1190.0	1276.8	1461.9	1522.2	1741.5	1870.7	2069.5	2403.4	2281.1	2666.3	2945.3	3330.3	3829.1	4070.9	4685.7	5386.5	6272.0	7199.5
S7	517.6	607.9	696.3	776.7	884.9	980.6	1164.2	1250.4	1395.6	1576.9	1811.3	2049.6	2272.6	2721.4	3156.4	3631.8	4337.9	4924.9
S8	360.8	412.1	482.7	549.4	621.4	674.3	802.7	842.3	921.1	1068.9	1240.3	1447.4	1531.1	1830.6	2164.1	2475.3	2980.8	3453.8
S9	384.6	452.4	512.0	562.9	636.5	716.0	798.5	878.8	954.1	1049.4	1175.7	1338.7	1504.4	1635.3	1911.8	2150.7	2486.7	2832.4
S10	352.0	380.3	432.6	473.9	527.8	563.4	626.0	705.1	728.2	817.6	933.8	1029.2	1135.0	1279.9	1497.8	1658.9	1952.6	2226.9
S11	212.8	224.2	252.1	259.3	294.1	308.4	346.1	374.9	378.9	416.9	484.6	557.1	611.0	661.4	775.9	876.3	1012.8	1201.3
S12	1368.0	1479.3	1744.9	1801.7	2051.7	2211.1	2471.6	2854.3	2837.2	3269.6	3763.1	4409.3	4883.8	5428.8	6563.2	7342.3	8934.2	10,339.3
S13	1047.5	1127.3	1263.9	1369.1	1569.6	1708.0	1855.4	2093.0	2183.5	2508.1	2801.1	3275.7	3786.2	4120.3	5038.4	6040.9	7141.6	8534.9
S14	683.0	745.7	808.9	890.2	983.4	1097.4	1215.9	1362.5	1450.0	1592.7	1766.5	2069.6	2359.7	2626.2	3115.8	3593.8	4163.7	4788.1
S15	459.0	516.6	583.1	636.7	734.6	802.1	897.5	1025.3	1082.3	1227.5	1382.3	1595.4	1798.8	2019.1	2424.1	2796.2	3292.9	3871.9
S16	1201.3	1345.4	1506.7	1663.6	1899.4	2072.4	2379.8	2688.9	2876.5	3135.1	3520.5	4075.6	4637.2	5204.1	6156.5	7162.2	8252.8	9670.8
S17	793.8	841.0	939.6	983.5	1096.2	1159.5	1280.1	1379.4	1408.8	1499.9	1717.4	1910.8	2111.6	2313.9	2657.5	2883.9	3404.0	3815.1
S18	662.5	737.7	847.6	929.8	1064.7	1184.8	1311.8	1551.8	1648.9	1866.8	2133.3	2474.9	2853.4	3243.1	3929.1	4545.1	5458.7	6474.8
S19	392.3	416.5	432.5	466.0	482.4	537.6	518.9	590.5	563.3	624.2	640.2	713.5	747.4	832.3	888.2	992.8	1087.7	1218.1
S20	116.2	127.3	141.3	151.3	165.2	174.4	189.4	213.0	218.5	241.9	267.8	293.4	316.6	348.0	402.3	435.2	507.5	573.3
S21	158.9	171.6	192.4	206.8	227.9	238.7	260.3	295.7	295.0	339.0	387.0	425.2	447.1	506.2	599.6	651.6	779.6	898.3
S22	46.1	51.3	54.7	63.8	68.2	80.6	91.6	103.9	112.8	127.4	144.1	175.0	200.5	233.0	277.6	321.6	380.9	433.4
S23	1107.4	1239.5	1431.2	1538.3	1731.5	1911.7	2177.5	2492.3	2593.5	2967.5	3343.3	3866.4	4370.9	4929.5	5789.0	6687.7	8171.9	9480.3
S24	154.0	173.0	205.6	220.1	270.0	293.2	348.8	395.2	417.8	476.3	575.9	680.5	790.5	882.3	1046.0	1248.2	1413.3	1761.5
S25	204.9	234.2	276.5	307.0	358.4	397.6	458.5	548.3	590.7	695.9	814.7	955.1	1102.8	1268.8	1547.7	1807.0	2222.4	2665.1
S26	344.8	336.2	360.3	359.9	389.8	387.0	397.5	415.7	395.0	419.2	450.1	484.4	510.8	523.9	594.9	649.6	713.5	797.8
S27	2791.7	3092.6	3604.9	3946.2	4674.1	5115.9	5928.0	6787.6	7133.1	8250.5	9830.2	11,604.1	13,366.6	15,185.3	18,422.4	21,749.1	26,097.7	31,852.5
S28	826.4	939.9	1110.3	1248.2	1473.2	1660.1	1928.0	2282.5	2402.8	2868.6	3381.3	4031.7	4697.4	5470.3	6684.0	7948.5	9801.1	11,841.8
S29	439.0	473.0	556.0	611.1	714.8	746.7	865.7	1005.2	1017.3	1189.2	1433.3	1634.8	1826.6	2116.6	2612.8	2969.3	3619.3	4396.6
S30	79.0	72.0	71.1	65.2	64.4	59.0	57.0	54.9	47.6	45.9	45.5	44.7	42.9	41.1	41.8	40.9	41.2	41.8
S31	8513.3	8816.1	10,758.2	11,946.7	14,457.5	15,267.7	18,383.9	20,926.4	20,882.5	24,058.3	29,217.8	34,314.2	39,827.2	46,281.4	56,028.5	65,250.1	78,024.5	95,014.2
S32	5079.5	5169.2	5743.5	5982.6	6612.1	6699.9	7268.2	7964.0	7636.9	8454.1	9479.1	10,399.5	11,110.2	12,059.2	13,929.5	15,182.7	17,414.8	19,827.3

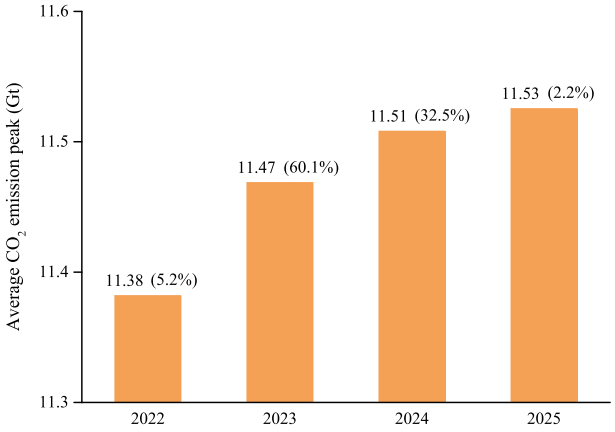

Fig. A1. CO_2 emission peak frequency of 10,000 Pareto solutions*. *The percentage in the parentheses indicates the CO_2 peak frequency of 10,000 Pareto solutions.

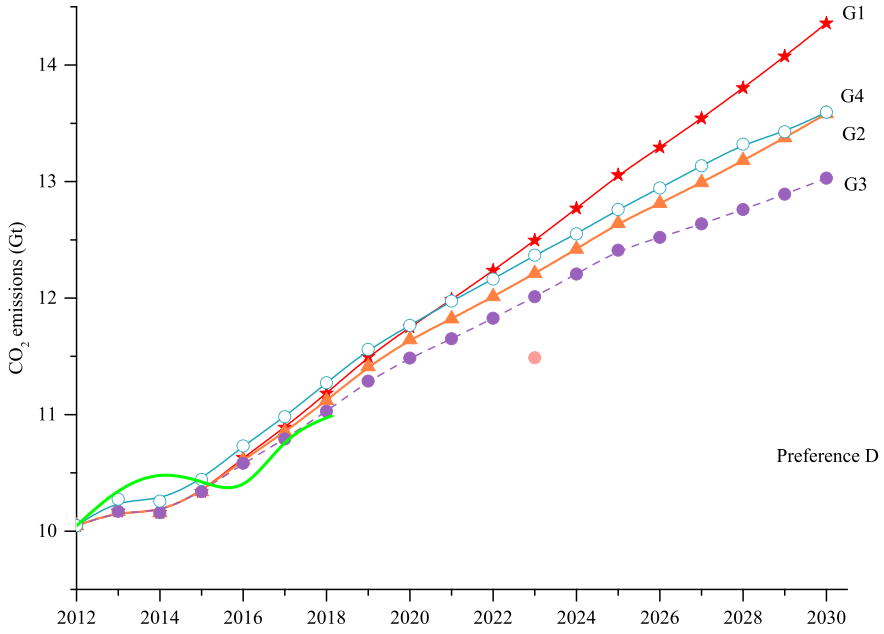

Fig. A2. CO_2 emissions trends in different scenarios GDP growth rate and industrial structure. The GDP growth rate settings in three different periods of 2016–2020, 2021–2025, and 2026–2030 are follows: G1: 6.7%, 6.0%, and 5.5%; G2:6.5%, 5.5% and 4.5%; G3:6.0%, 5.0%, and 5.4%. The rates of G4 are same with the present study optimized results are 6.9%, 5.5%, and 4.8%.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2018.05.012.

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